

Wireless Multimedia Sensor Network for plant disease detections

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Abstract—To minimize pesticide use it is necessary to detect at the early stage the present of plant disease and perform local treatment instead of global systematic treatment. To achieve this goal, one of the techniques may be used is image processing through the deployment of WMSN in the cultivated field. However, transmitting massive image data wirelessly will increase significantly network traffic and particularly energy consumption. In this paper, we propose a plant disease detection approach which is designed to run on the resource-constrained WMSN nodes. Through the analysis of plant images acquired by the node, this new approach is able to make a preliminary local decision on the health condition of the plant and determine the necessity of sending back images to the control centre for further inspection, thus improving the efficiency of the monitoring network. The complete method includes image segmentation based on both color and shape, and uses 2D histogram as the feature for classification. Experiments on the plant images with nutrient deficiency symptoms show the classification accuracy of the new method reaches 87.5%.

I. INTRODUCTION

In agriculture practice, being able to detect plant diseases at their early stage can usually prevent major losses on the farmland yields [1,2,3]. This work has been done by doing sampling inspection on the large farmland manually, which is a costly and demanding process. In recent years, the rapid development of Wireless Multimedia Sensor Network (WMSN) provides a new support to this task that has the potential of reducing the workload substantially. The wireless multimedia sensor network node is equipped with a low cost CCD camera and is able to take and send back images of its deployment location[4]. After WMSN has been deployed on the farmland, the inspector only needs to distinguish crop images on the computer to obtain the information on crop growth.

Considering the resource constraints on WMSN like computation power, network bandwidth, energy consumption and the workload of each WMSN node, it is not a good idea to let every node to send back the image frequently. Therefore if the inspection interval (sample frequency) is too long, plant disease may spread in large scale during the interval. To solve this dilemma, we propose a solution based on a plant disease detection program running on each nodes of the WMSN, which automatically inspects the newly taken plant images and determines whether the plant has the risk of infection. Under this mechanism, the WMSN can take plant photos at a higher frequency, but the amount of data to be transferred is reduced.

Compared with the plant disease detection programs designed for botany laboratories [5, 6], the program of the same function for WMSN has many disadvantages in its available system resources. For example, input images taken in laboratories have higher quality and usually come with a controlled background, which eliminates the work of locating target areas, but the plant images taken by WMSN node on farmlands have a relatively more complex background. Besides, the constrain on power consumption and processor capability of a WMSN limits the complexity of the programs running on it[7].

Due to the high resource constraints described above, we tend to choose algorithms with less computation complexity to construct the detection program instead of using existing complex algorithms which can provide better performances. For example, we use binarization to find regions of interest instead of clustering-based image segmentation algorithms. And in the classification part, the result is based on comparing the distance of the feature vector to the cluster centroids. However, experiments have shown after carefully tuning the parameters, our method can still reach a satisfied result.

This paper is organized as follows: Section II gives a detailed description of the proposed method, which includes image segmentation, feature extraction and classification. In the next section, we give the experimental results of the new method on detection accuracy and computational complexity. The last section gives a conclusion and describes the future work.

II. METHODOLOGY

The overall structure of the plant disease detection program we designed for WMSN is given in fig. 1. It includes 3 major parts: image segmentation part extracts the regions correspond with plants from the input image, the feature extraction part converts the segmentation results into feature vectors, and finally the classification part decides whether the plant in the input image is sick based on comparing the feature information of the input with the training examples.



Fig. 1. Overall structure of the plant disease detection program for WMSN

In the following parts of this section, we are going to demonstrate our approach with a picture of strawberry white spot disease shown in fig. 2. This picture contains flower, fruit, both healthy and sick leaves in it and a large part of it is plastic sheeting with mud. It's a typical scenario which will possibly be taken by the camera on a WMSN node, thus our approach can have a relatively comprehensive evaluation. The picture is encoded in the JPEG format.



Fig. 2. Strawberry white spot disease

A. Image segmentation

The ideal result of image segmentation for a plant disease detection system is to preserve only the infected area in the output image. However, due to the diversity in the types of the diseases, the differences in growth environment of the plants and many other factors, the final symptoms are hard to predict. In order to achieve better results, plant disease detection algorithms are usually targeted on one or a group of particular symptoms.

Moreover any of these areas on plants can be separated by exploiting 2 different kinds of information: the color information and the spatial information (location and shape of the infected area). In the detection program we proposed, the utilization of both color and spatial information have been achieved by binarization in the HSV color space and

morphological operations respectively. To be more specific, we used color information to detect the existence and rough location of the plant in the input image, and morphological operations to predict the location of potentially infected areas in relation to the plant. The whole image segmentation process is given in fig. 3.

1) *Color based rough image segmentation:* The HSV color space has been widely used in image segmentation algorithms because, compared with the RGB color space, it is more based on human color perception and separates the color information from other less robust features such as illumination. By converting the input image to the HSV color space, we can determine a specific color region using upper and lower thresholds in the hue color plane which identify the typical color of the target plant.

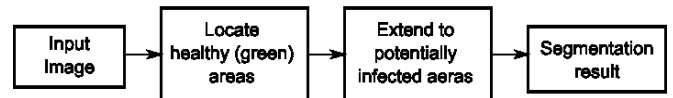
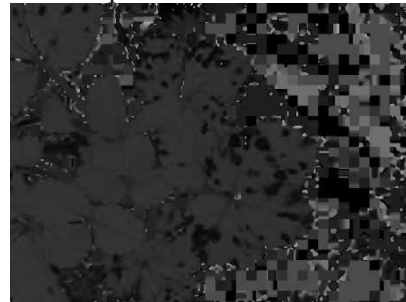


Fig. 3. Steps in the image segmentation process

Fig. 4(a) and 4(b) each demonstrates the hue and saturation image plane in the HSV color space of the image in fig. 2 respectively. From fig. 4(a) we can see although the hue image is able to identify the color of strawberry leaves, it also strengthens the JPEG compression noise in the low saturation parts of the image, which ends up in a group of random color mosaics on the hue image (see the right part of fig. 4(a)). To solve this problem, we also set thresholds on the saturation image (fig. 4(b)) to create an image mask which points out the high saturation parts in the input image. By combining the binarization results of both hue and saturation image, the noisy parts can be filtered out while the segmentation result of the plants on hue image is preserved. Finally, since water drops and leaf reflection often create glares in the image acquired, we set thresholds on the value image to eliminate the influence of these parts.



(a)



(b)

Fig. 4. Hue (a) and saturation (b) image plane of the strawberry white spot disease image

The final result of binarization in the HSV color space is shown in fig. 6(a). From the image we can see the rough segmentation is able to acquire the locations of green leaves in the input image. In the next morphological processing part of the image segmentation, we are going to demonstrate the methodology of acquiring leaf spots with this intermediate result.

2) Refine segmentation result with morphological operations: The plant disease detection program running on WMSN aims at detecting a variety of diseases. However the infected areas of different diseases have little in common in terms of texture, color and shape. This diversity makes it difficult to generalize the priori information of the infected areas for image segmentation from a color point of view.

Our approach of solving this problem is based on the location priori of the infected areas on the sick plant. In the program, we model the shape of a healthy leaf on the plant as a convex polygon. As a result, once the leaf has been infected and the infected areas are no longer green, its color-based segmentation result will generate a concave polygon or a polygon with a hole in it. If we use the morphological close operation refill these holes and caves, the recovered area can then be considered as the location of infected areas.

Fig. 5 gives the flowchart of the morphological refine process in our system. In order to remove noise pixels, a morphological open operation has been added before the close operation. Since not all healthy leaves can be considered as convex polygons, the core size for both open and close operations should be choose carefully in order to fill the holes created by the lesion instead of merging the gaps between different parts of the leaf. Taking into account that plant diseases can not only create spots on leaves, but also change the color of healthy leaves, the green leaf parts are not removed from in the final segmentation result. Instead, we consider these parts to have some information about the pathological changes as well.



Fig. 5. Steps in the image segmentation process

B. Feature extraction & classification

In the image segmentation step, we have obtained a picture of the plant which possibly has infected areas on its leaves. To detect the existence of these areas with machine learning methods, feature selection is a critical step. Image features can be grouped into three major categories: color, shape and texture. Since the shape of the damaged areas on an infected plant could be irregular, shape based features has poor robustness in detecting plant diseases. And because features based on texture require a lot of computation to create texture models, they are not suitable for implementation on the WMSN either.

Histogram feature is a commonly used feature in many image recognition algorithms, including plant disease detection[8]. It reflects the statistical properties of the values of pixels in an image regardless of their locations[9]. And it's also easy to compute. Here in this program, we use the hue and saturation image masked by the segmentation result of the previous step to generate a H-S 2D histogram as the feature of the input image. By concatenating the 2D histogram matrix into a vector, the difference between histograms can be measured through calculating the Euclidean distance between their corresponding vectors.

When selecting the classification algorithm, also in consideration of the computational complexity of the program, we base it on the distance between the feature vector of the input image and the centroids of the training datasets. The centroids of the training data are computed using the following method: In the training process, each image also goes through the same segmentation and calculation process as test images to make sure their feature vectors are obtained under the same condition. After all the feature vectors of the training images have been computed, the training program then calculates the mean value of both positive and negative training images and gets two centroids of the training data. Since in this classification approach, we only needs to compute and compare 2 distances to get the final result, it introduces very little system overhead.



(a)



(b)

Fig. 6. Intermediate (a) and final (b) segmentation results of the image segmentation program

C. Program Implementation

In the implementation part, we choose the MiLive platform described in [4] as the target WMSN platform of our disease detection program. This WMSN node is equipped with a low cost CCD camera to acquire static plant images in Full HD resolution. It uses an ARM11 core on the integrated Raspberry Pi board as its main processing power. An embedded Linux system has been installed on the Raspberry Pi board so the application programs can be easily transplanted to the MiLive platform.

To reduce program complexity and system overhead, we implement our program based on the C language and the OpenCV library. In the final implementation of our proposal: program, flowchart of the image segmentation and feature extraction parts are given in fig. 7.

In fig. 7, different functional blocks of the program are divided by red dotted lines. Input data and parameters are labelled in blue, while the output data are labelled in green.

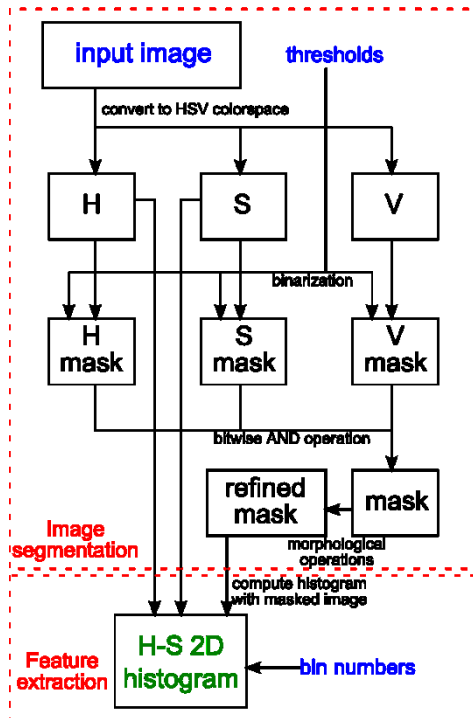


Fig. 7. Steps in the image segmentation process

Once the program receives an input image, it converts the image into HSV color space and applies upper and lower thresholds on each of the three image planes as described at the beginning of this chapter. Three binarized results are combined together through AND operation to create a mask representing the region of interest. This mask is refined by morphological open and then close operations to remove noise and locate the potentially infected areas. Finally, the histogram computation program uses the pixels labelled by the refined mask in the original H and S image to compute 2D histogram as the image feature.

The training program runs on a more sophisticated platform such as the computers. Once the two centroids of the training datasets have been computed, they are saved in a xml file and transferred to the WMSN. In the classification step on WMSN, the detection program restores the two centroids to compare them with the incoming feature vector to get the final result.

III. EXPERIMENTAL RESULTS

In the following experiments, we will demonstrate both the intermediate and final results of detecting the nutrient deficiency symptom on the plant with the new method. This symptom performs as irregular yellow spots on plant leaves, as shown in fig. 8(a). The resolution for all the test images is 640×480 .



(a)

(b)

Fig. 8. An image of the nutrient deficiency symptom (a) compared with the segmentation result of this image (b)

A. Image segmentation results

In the image segmentation part, the thresholds set for binarization are listed in table I. For each pixel of the image in HSV color space, when its 3 channel values all fall between the upper and lower thresholds of the corresponding channel, it is considered as a valid pixel and will be copied to the mask. In the morphological operation step, circular cores have been used as the core of both open and close operation. The radius of the core for open operation is 3 pixels, while for the close operation, it is 30 pixels.

The result of segmentation is shown in fig. 8(b), in which we can find that most part of the background has been

excluded, but the plant and especially the damage spot were well preserved.

TABLE I
BINARIZATION THRESHOLDS

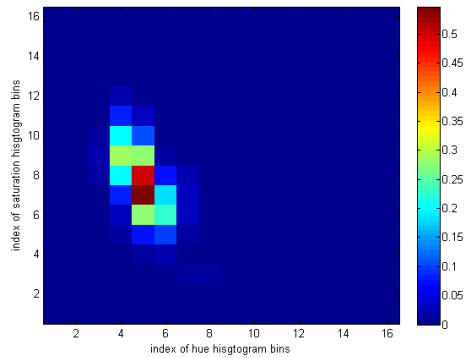
Image Plane	Range	Upper threshold	Lower threshold
Hue	0~359	180	60
Saturation	0~255	255	70
Value	0~255	200	50

B. Plant disease detection results

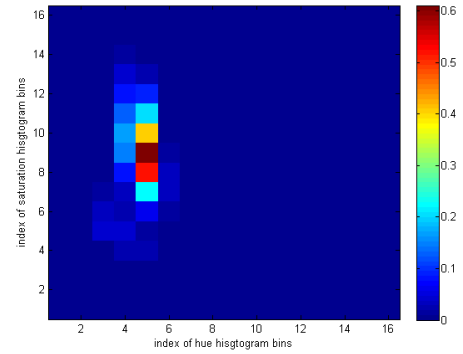
In the disease detection part, we choose 32 different images as the training image for our program. The positive and negative training datasets each contains 16 images. The 2D histogram feature uses 16 bins on both hue and saturation dimensions.

The two centroids of the training data, which are the mean values of both the positive and negative training datasets, are visualized as images in fig. 9. In the two images of fig.9, each block corresponds with a bin in the 2D histogram, and the color of the block corresponds with the percentage of total pixels which fall into this interval.

In order to test the classification accuracy, we used 16 different test images as input and recorded the output of the program. The results are listed in table II. For sick plant image inputs, the classification accuracy of the program is 87.5%, while for healthy plant image inputs, the accuracy is 75%. The test results prove the effectiveness of the plant disease detection program.



(a)



(b)

Fig. 9. Visualized mean 2D histogram of both positive training dataset (a) and negative training dataset (b)

TABLE II
CLASSIFICATION ACCURACY ON THE NUTRIENT DEFICIENCY SYMPTOM IMAGES OF PLANTS

Input Image Type	Number of Images	Number of Correct Recognitions	Classification Accuracy
Sick Plants	8	7	87.5%
Healthy Plants	8	6	75%

IV. CONCLUSION

Based on the high resource constraints of WMSN, particularly the hardware key features of MiLive platform, we proposed a new plant disease detection method optimized for WMSNs. This new method is able to separate different plants from complex backgrounds and has robustness face to environment changes such as illumination. Its classification result can achieve a high accuracy on the images of sick plants.

However, the current algorithm still needs to run more tests to verify its classification adaptability with different plant disease types. Moreover it's important to evaluate the performance of the proposed method on the real-world deployment in a cultivated field. Thus in cooperation with IRSTEA MiLive platform containing 20 nodes will be deployed at Montoldre in Allier (France).

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